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APPLICATIONS OF DEEP LEARNING AND MACHINE LEARNING IN HEALTHCARE DOMAIN – A LITERATURE REVIEW

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ABSTRACT

Artificial intelligence (AI) has been developing rapidly in recent years in terms of software algorithms, hardware implementation, and applications in a vast number of areas. In this review, we summarize the latest developments of applications of AI in biomedicine, including disease diagnostics, living assistance, biomedical information processing, and biomedical research. Various automated systems and tools like Brain-computer interfaces (BCIs), arterial spin labelling (ASL) imaging, ASL-MRI, biomarkers, Natural language processing (NLP) and various algorithms helps to minimize errors and control disease progression. The computer assisted diagnosis, decision support systems, expert systems and implementation of software may assist physicians to minimize the intra and inter-observer variability. In this paper, a detailed literature review on application and implementation of Machine Learning, Deep Learning and Artificial Intelligence in the healthcare industry by various researchers.

Keywords: Healthcare, Machine Learning, Deep Learning, Artificial Intelligence, Disease Severity, Survival prediction, Big data

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1. INTRODUCTION

Artificial intelligence (AI) [1] is defined as the intelligence of machines, as opposed to the intelligence of humans or other living species. AI can also be defined as the study of ‘‘intelligent agents”—that is, any agent or device that can perceive and understand its surroundings and accordingly take appropriate action to maximize its chances of achieving its objectives. AI also

refers to situations wherein machines can simulate human minds in learning and analysis, and thus can work in problem solving. This kind of intelligence is also referred to as machine learning (ML) [2].

We are living in the age of algorithms, in which machine learning (ML)/deep learning (DL) systems have transformed multiple industries such as manufacturing, transportation, and governance. Over the past few years, DL has provided state of the art performance in different domains—e.g., computer vision, text analytics, and speech processing, etc. Due to the extensive deployment of ML/DL algorithms in various domains (e.g., social media), such technology has become inseparable from our routine life. ML/DL algorithms are now beginning to influence healthcare as well—a field that has traditionally been impervious to large-scale technological disruptions [3]. ML/DL techniques have shown outstanding results recently in versatile tasks such as recognition of body organs from medical images, classification of interstitial lung diseases, detection of lungs nodules, medical image reconstruction, and brain tumor segmentation, to name a few [4]. It is highly expected that intelligent software will assist radiologists and physicians in examining patients soon and ML will revolutionize the medical research and practice. Clinical medicine has emerged as an exciting application area for ML/DL models, and these models have already achieved human-level performance in clinical pathology, radiology, ophthalmology, and dermatology [5].

The potential of ML models for healthcare applications is also benefitting from the progress in concomitantly advancing technologies like cloud/edge computing, mobile communication, and big data technology [6]. Together with these technologies, ML/DL can produce highly accurate predictive outcomes and can facilitate the human-centered intelligent solutions [7]. Along with other benefits like enabling remote healthcare services for rural and low-income zones, these technologies can play a vital role in revitalizing the healthcare industry.

2. MACHINE LEARNING IN HEALTHCARE

The major phases for developing a ML-based healthcare system are illustrated and major types of ML/DL that can be used in healthcare applications are briefly described next.

2.1. Un-Supervised Machine Learning

The ML techniques utilizing unlabelled data are known as unsupervised learning methods. Widely used examples of unsupervised learning methods are a clustering of data points using a similarity metric and dimensionality reduction to project high dimensional data to lower-dimensional subspaces (sometimes also referred to as feature selection). In addition, unsupervised learning can be used for anomaly detection, e.g., clustering [8]. Classical examples of unsupervised learning methods in healthcare and prediction of hepatitis disease using principal component analysis (PCA) which is a dimensionality reduction technique [9].

2.2. Supervised Machine Learning

Such methods that build or map the association between the inputs and outputs using labeled training data are characterized as supervised learning methods [10]. If the output is discrete then the task is called classification and for a continuous value output, the task is called regression. Classical examples of supervised learning methods in healthcare include the classification of different types of lung diseases (nodules) and recognition of different body organs from medical images. Sometimes, ML methods can be neither supervised nor unsupervised, i.e., where the training data contains both labeled and unlabelled samples. Methods utilizing such data are known as semi-supervised learning methods.

2.3. Semi-Supervised Machine Learning

Semi-supervised learning methods are useful when both labelled and unlabelled samples are available for training, typically, a small amount of labelled data and a large amount of unlabelled data. Semi-supervised learning techniques can be particularly useful for a variety of healthcare applications as acquiring enough labelled data for model training is difficult in healthcare.

2.4. Reinforcement Learning

Methods that learn a policy function given a set of observations, actions, and rewards in response to actions performed over time fall in the class of reinforcement learning (RL) [11]. RL has a great potential to transform many healthcare applications and recently, it has been used for context-aware symptoms checking for disease diagnosis.

3. APPLICATIONS OF MACHINE LEARNING IN HEALTHCARE

Healthcare service providers generate a large amount of heterogeneous data and information daily, making it difficult for the “traditional methods” to analyze and process it. ML/DL methods help to effectively analyze this data for actionable insights. In addition, there are heterogeneous sources of data that can augment healthcare data such as genomics, medical data, data from social media, and environmental data, etc.

3.1. Applications of ML in Prognosis

Prognosis is the process of predicting the expected development of a disease in clinical practice. It also includes identification of symptoms and signs related to a specific disease and whether they will become worse, improve, or remain stable over time and identification of potential associated health problems, complications, ability to perform routine activities, and the likelihood of survival. As in clinical setting, multi-modal patients’ data is collected, e.g., phenotypic, genomic, proteomic, pathology tests results, and medical images, etc., which can empower the ML models to facilitate disease prognosis, diagnosis and treatment. For instance, ML models have been largely developed for the identification and classification of different types of cancers, e.g., brain tumor and lung nodules. However, the potential applications ML for disease prognosis, i.e., prediction of disease symptoms, risks, survivability, and recurrence have been exploited under recent translational research efforts that aim to enable personalized medicine. However, the field of personalized medicine is nascent that requires extensive development of adjacent fields like bioinformatics, strong validation strategies, and demonstrably robust applications of ML thus to achieve the huge and translational impact.

3.2. Applications of ML in Diagnosis

3.2.1. Electronic Health Records

Hospitals and other healthcare service providers are producing a large collection of electronic health records (EHRs) on a daily basis and comprise of structured and unstructured data that contains a complete medication history of patients. ML-based methods have been utilized for the extraction of clinical features for facilitating the diagnosis process [12].

3.2.2. ML in Medical Image Analysis

In medical image analysis [13], ML techniques are used for efficient and effective extraction of information from medical images that are acquired using different imaging modalities such as magnetic resonance imaging (MRI), computed tomography (CT), ultrasound, and positron emission tomography (PET), etc. These modalities provide important functional and anatomical information about different body organs and play a crucial role in the detection/localization and

diagnosis of abnormalities. The key purpose of medical image analysis is to assist clinicians and radiologists for efficient diagnosis and prognosis of the diseases. The prominent tasks in medical image analysis include detection, classification, segmentation, retrieval, reconstruction, and image registration.

3.3. Applications of ML in Treatment

3.3.1. Image Interpretation

Medical images are widely used in the routine clinical practice and the analysis and interpretation of these images are performed by expert physicians and radiologists. To narrate the findings regarding images being studied, they write textual radiology reports about each body organ that was examined in the conducted study. However, writing such reports is very challenging in some scenarios, e.g., less experienced radiologists and healthcare service providers in rural areas where the quality of healthcare services is not up to the mark. On the other side, for experienced radiologists and pathologists, the process of preparing high-quality reports can be tedious and time-consuming which can be exacerbated by many patients visiting daily. Therefore, various researchers have attempted to address this problem using natural language processing (NLP) and ML techniques [14].

3.3.2. Real-time Health Monitoring

Real-time monitoring of critical patients is crucial and is a key component of the treatment process. Continuous health monitoring using wearable devices, IoT sensors, and smartphones is gaining interest among people. In a typical setting of continuous health monitoring, health data is collected using a wearable device and smartphone and then transmitted to the cloud for analysis using an ML/DL technique [15].

3. LITERATURE REVIEW

Almansour, Njoud Abdullah, et al [16] aimed to assist in the prevention of Chronic Kidney Disease (CKD) by utilizing machine learning techniques to diagnose CKD at an early stage. Kidney diseases are disorders that disrupt the normal function of the kidney. As the percentage of patients affected by CKD is significantly increasing, effective prediction procedures should be considered. The authors focused on applying different machine learning classification algorithms to a dataset of 400 patients and 24 attributes related to diagnosis of chronic kidney disease. The classification techniques used in this study include Artificial Neural Network (ANN) and Support Vector Machine (SVM). To perform experiments, all missing values in the dataset were replaced by the mean of the corresponding attributes. Then, the optimized parameters for the Artificial Neural Network (ANN) and Support Vector Machine (SVM) techniques were determined by tuning the parameters and performing several experiments. The final models of the two proposed techniques were developed using the best-obtained parameters and features.

Belić, Minja, et al [17] aimed to give a comprehensive, high-level overview of applications of artificial intelligence through machine learning algorithms in kinematic analysis of movement disorders, specifically Parkinson’s disease (PD). The authors surveyed papers published between January 2007 and January 2019, within online databases, including PubMed and Science Direct, with a focus on the most recently published studies. The search encompassed papers dealing with the implementation of machine learning algorithms for diagnosis and assessment of PD using data describing motion of upper and lower extremities. The authors presented an overview of 48 relevant studies published in the abovementioned period, which investigate the use of artificial intelligence for diagnostics, therapy assessment and progress prediction in PD based on body kinematics. Different machine learning algorithms

showed promising results, particularly for early PD diagnostics. The investigated publications demonstrated the potentials of collecting data from affordable and globally available devices.

Liang, Huiying, et al [18] showed that Machine Learning Classifiers (MLCs) can query Electronic Health Records (EHRs) in a manner similar to the hypothetico-deductive reasoning used by physicians and unearth associations that previous statistical methods have not found. The proposed model applied an automated natural language processing system using deep learning techniques to extract clinically relevant information from EHRs. The proposed model demonstrates high diagnostic accuracy across multiple organ systems and is comparable to experienced pediatricians in diagnosing common childhood diseases. This study provided a proof of concept for implementing an AI-based system as a means to aid physicians in tackling large amounts of data, augmenting diagnostic evaluations, and to provide clinical decision support in cases of diagnostic uncertainty or complexity.

Wu, Chieh-Chen, et al [19] aimed to develop a machine learning model to predict Fatty Liver Disease (FLD) that could assist physicians in classifying high-risk patients and make a novel diagnosis, prevent and manage FLD. FLD is a common clinical complication; it is associated with high morbidity and mortality. However, an early prediction of FLD patients provides an opportunity to make an appropriate strategy for prevention, early diagnosis, and treatment.

Jo, Taeho, Kwangsik Nho, and Andrew J. Saykin [20] performed a systematic review of publications using deep learning approaches and neuroimaging data for diagnostic classification of Alzheimer Disease (AD). PubMed and Google Scholar search was used to identify deep learning papers on AD published between January 2013 and July 2018. These papers were reviewed, evaluated, and classified by algorithm and neuroimaging type, and the findings were summarized. Of 16 studies meeting full inclusion criteria, 4 used a combination of deep learning and traditional machine learning approaches, and 12 used only deep learning approaches. The combination of traditional machine learning for classification and stacked auto-encoder (SAE) for feature selection produced accuracies of up to 98.8% for AD classification and 83.7% for prediction of conversion from mild cognitive impairment (MCI), a prodromal stage of AD, to AD. Deep learning approaches, such as convolutional neural network (CNN) or recurrent neural network (RNN), that use neuroimaging data without pre-processing for feature selection have yielded accuracies of up to 96.0% for AD classification and 84.2% for MCI conversion prediction. The best classification performance was obtained when multimodal neuroimaging and fluid biomarkers were combined. Deep learning approaches continue to improve in performance and appear to hold promise for diagnostic classification of AD using multimodal neuroimaging data.

Ngiam, Kee Yuan, and Wei Khor [21] exploited a capability such as deep neural networks, machine learning presents a powerful tool for analysing large amounts of complex health-care data to improve the efficiency and cost-effectiveness of health-care delivery. When used to augment the capabilities of doctors, machine learning can perform routine, systematic tasks with high consistency, freeing up doctors’ time so that they can address clinical problems that are more complex or that require substantial human interaction.

Kawakami, Eiryo, et al [22] aimed to develop an ovarian cancer–specific predictive framework for clinical stage, histotype, residual tumor burden, and prognosis using machine learning methods based on multiple biomarkers. Overall, 334 patients with epithelial ovarian cancer (EOC) and 101 patients with benign ovarian tumors were randomly assigned to "training" and "test" cohorts. Seven supervised machine learning classifiers, including Gradient Boosting Machine (GBM), Support Vector Machine, Random Forest (RF), Conditional RF (CRF), Naive Bayes, Neural Network, and Elastic Net, were used to derive diagnostic and

prognostic information from 32 parameters commonly available from pre-treatment peripheral blood tests and age.

Abdar, Moloud, et al [23] describe an innovative machine learning methodology that enables an accurate detection of Coronary artery disease (CAD) and applied it to data collected from Iranian patients. The authors first tested ten traditional machine learning algorithms, and then the three-best perform- ing algorithms (three types of SVM) were used in the rest of the study. To improve the performance of these algorithms, a data pre-processing with normalization was carried out. Moreover, a genetic algorithm and particle swarm optimization, coupled with stratified 10-fold cross-validation, were used twice: for optimization of classifier parameters and for parallel selection of features.

Kwon, Joon-myoung, et al [24] aimed to develop and validate deep-learning-based artificial intelligence algorithm for predicting mortality of AHF (DAHF). DAHF predicted the in-hospital and long-term mortality of patients with AHF more accurately than the existing risk scores and other machine-learning models.

Kiely, David G., et al [25] explored whether a predictive model based on healthcare resource utilisation can be used to screen large populations to identify patients at high risk of idiopathic pulmonary arterial hypertension. Hospital Episode Statistics from the National Health Service in England, providing close to full national coverage, were used as a measure of healthcare resource utilisation. Data for patients with idiopathic pulmonary arterial hypertension from the National Pulmonary Hypertension Service in Sheffield were linked to pre-diagnosis Hospital Episode Statistics records. This study highlighted the potential application of artificial intelligence to readily available real-world data to screen for rare diseases such as idiopathic pulmonary arterial hypertension. This algorithm could provide low-cost screening at a population level, facilitating earlier diagnosis, improved diagnostic rates and patient outcomes. Studies to further validate this approach are warranted.

Makino, Masaki, et al [26] constructed a new predictive model for diabetic kidney diseases (DKD) using AI, processing natural language and longitudinal data with big data machine learning, based on the electronic medical records (EMR) of 64,059 diabetes patients. AI extracted raw features from the previous 6 months as the reference period and selected 24 factors to find time series patterns relating to 6-month DKD aggravation, using a convolutional autoencoder. AI constructed the predictive model with 3,073 features, including time series data using logistic regression analysis. AI could predict DKD aggravation with 71% accuracy.

Shamai, Gil, et al [27] developed a machine learning model termed morphological-based molecular profiling (MBMP). Logistic regression was used to explore correlations between histomorphology and biomarker expression, and a deep convolutional neural network was used to predict the biomarker expression in examined tissues.

Ding, Yiming, et al [28] used Convolutional neural network of InceptionV3 architecture was trained on 90% of ADNI data set and tested on the remaining 10%, as well as the independent test set, with performance compared to radiologic readers. Model was analyzed with sensitivity, specificity, receiver operating characteristic (ROC), saliency map, and *t*-distributed stochastic neighbor embedding. The authors developed and validated a deep learning algorithm that predicts the final diagnosis of Alzheimer disease (AD), mild cognitive impairment, or neither at fluorine 18 (18F) fluorodeoxyglucose (FDG) PET of the brain and compare its performance to that of radiologic readers.

Shen, Jiayi, et al [29] aimed to systematically examine the literature, in particular, focusing on the performance comparison between advanced AI and human clinicians to provide an up-to-date summary regarding the extent of the application of AI to disease diagnoses. By doing so, this review discussed the relationship between the current advanced AI development and clinicians with respect to disease diagnosis and thus therapeutic development in the long run.

The authors systematically searched articles published between January 2000 and March 2019 following the Preferred Reporting Items for Systematic reviews and Meta-Analysis in the following databases: Scopus, PubMed, CINAHL, Web of Science, and the Cochrane Library. According to the preset inclusion and exclusion criteria, only articles comparing the medical performance between advanced AI and human experts were considered.

Seetharam, Karthik, Sirish Shrestha, and Partho P. Sengupta [30] highlighted noteworthy examples of machine learning utilization in echocardiography, nuclear cardiology, computed tomography, and magnetic resonance imaging over the past year. In the past year, machine learning (ML) has expanded its boundaries in cardiology with several positive results. Some studies have integrated clinical and imaging information to further augment the accuracy of these ML algorithms. The authors mentioned in this review have clearly demonstrated superior results of ML in relation to conventional approaches for identifying obstructions or predicting major adverse events about conventional approaches.

Das, Arun, et al [31] presented a scalable cloud based teleophthalmology architecture via the Internet of Medical Things (IoMT) for diagnosis of Age-related Macular Disease (AMD). In the proposed architecture, patients wear a head-mounted camera (OphthoAI IoMT headset) to send their retinal fundus images to their secure and private cloud drive storage for personalized disease severity detection and predictive progression analysis. A proposed AMD-ResNet convolution neural network with 152 layers will then analyze the images to identify and determine AMD disease severity.

Ting, Daniel Shu Wei, et al [32] provided a summary of the state-of-the-art Deep Learning (DL) systems described for ophthalmic applications, potential challenges in clinical deployment and the path forward. Artificial intelligence (AI) based on deep learning (DL) has sparked tremendous global interest in recent years. DL has been widely adopted in image recognition, speech recognition and natural language processing, but is only beginning to impact on healthcare. In ophthalmology, DL has been applied to fundus photographs, optical coherence tomography and visual fields, achieving robust classification performance in the detection of diabetic retinopathy and retinopathy of prematurity, the glaucoma-like disc, macular oedema and age-related macular degeneration. DL in ocular imaging may be used in conjunction with telemedicine as a possible solution to screen, diagnose and monitor major eye diseases for patients in primary care and community settings.

Wong, Zoie SY, Jiaqi Zhou, and Qingpeng Zhang [33] aimed to highlight the opportunities gained through the use of Artificial Intelligence (AI) methods to enable reliable disease-oriented monitoring and projection in this information age. Since the beginning of the 21st century, the amount of data obtained from public health surveillance has increased dramatically due to the advancement of information and communications technology and the data collection systems now in place.

Myszczynska, Monika A., et al [34] discussed how machine learning can aid early diagnosis and interpretation of medical images as well as the discovery and development of new therapies. A unifying theme of the different applications of machine learning is the integration of multiple high- dimensional sources of data, which all provide a different view on disease, and the automated derivation of actionable insights.

Banerjee, Abhirup, et al [35] aimed to use machine learning, an artificial neural network (ANN) and a simple statistical test to identify SARS-CoV-2 positive patients from full blood counts without knowledge of symptoms or history of the individuals. The authors found that with full blood counts random forest, shallow learning and a flexible ANN model predict SARS-CoV-2 patients with high accuracy between populations on regular wards (AUC = 93-94%) and those not admitted to hospital or in the community (AUC = 80-86%). Here AUC is the Area Under the receiver operating characteristics Curve and a measure for model

performance. Moreover, a simple linear combination of 4 blood counts can be used to have an AUC of 85% for patients within the community. The normalised data of different blood parameters from SARS-CoV-2 positive patients exhibit a decrease in platelets, leukocytes, eosinophils, basophils and lymphocytes, and an increase in monocytes.

Huang, Shigao, et al [36] reviewed the literature on the application of AI to cancer diagnosis and prognosis and summarizes its advantages. The authors explored how AI assists cancer diagnosis and prognosis, specifically with regard to its unprecedented accuracy, which is even higher than that of general statistical applications in oncology. The authors also demonstrated ways in which these methods are advancing the field. Finally, opportunities and challenges in the clinical implementation of AI are discussed. Hence, the authors provided a new perspective on how AI technology can help improve cancer diagnosis and prognosis, and continue improving human health in the future.

Shen, Jiayi, et al [37] aimed to investigate the implementation of a well-performing AI algorithm in GDM diagnosis in a setting, which requires fewer medical equipment and staff and to establish an app based on the AI algorithm. The authors also explored possible progress if our app is widely used. Gestational diabetes mellitus (GDM) can cause adverse consequences to both mothers and their newborns. However, pregnant women living in low- and middle-income areas or countries often fail to receive early clinical interventions at local medical facilities due to restricted availability of GDM diagnosis. The outstanding performance of artificial intelligence (AI) in disease diagnosis in previous studies demonstrates its promising applications in GDM diagnosis.

Santo, Briana A., Avi Z. Rosenberg, and Pinaki Sarder [38] The primordial digital pathology informatics work employed classical image analysis and machine learning to prognosticate renal disease. Although this classical approach demonstrated tremendous potential, subsequent advancements in hardware technology rendered artificial neural networks '(ANNs) the method of choice for machine vision in computational pathology'. Offering rapid and reproducible detection, characterization and classification of kidney morphology, ANNs have facilitated the development of diagnostic and prognostic applications. In addition, modern machine learning with ANNs has revealed novel biomarkers in kidney disease, demonstrating the potential for machine vision to elucidate novel pathologic mechanisms beyond extant clinical knowledge.

Kaul, Vivek, Sarah Enslin, and Seth A. Gross [39] presents a brief historical perspective on the evolution of AI over the last several decades and the introduction and development of AI in medicine in recent years. A brief summary of the major applications of AI in gastroenterology and endoscopy are also presented.

Chu, Chui S., et al [40] The natural history of oral squamous cell carcinoma (OSCC) is complicated by progressive disease including loco-regional tumour recurrence and development of distant metastases. Accurate prediction of tumour behaviour is crucial in delivering individualized treatment plans and developing optimal patient follow-up and surveillance strategies. Machine learning algorithms may be employed in oncology research to improve clinical outcome prediction. Retrospective review of 467 OSCC patients treated over a 19-year period facilitated construction of a detailed clinicopathological database. 34 prognostic features from the database were used to populate 4 machine learning algorithms, linear regression (LR), decision tree (DT), support vector machine (SVM) and k-nearest neighbours (KNN) models, to attempt progressive disease outcome prediction. Principal component analysis (PCA) and bivariate analysis were used to reduce data dimensionality and highlight correlated variables. Models were validated for accuracy, sensitivity and specificity, with predictive ability assessed by receiver operating characteristic (ROC) and area under the curve (AUC) calculation.

Kovačević, Živorad, et al [41] presented the result of application of machine learning (ML) techniques in management of infant incubators in healthcare institutions. A total of 140 samples was used for development of Expert system based on ML classifiers. These samples were collected during 2015–2017 period, as part of yearly inspections of incubators in healthcare institutions by ISO 17020 accredited laboratory. Dataset division 80–20 was used for classifiers development and validation. Performance of the following machine learning algorithms was investigated: Naïve Bayes (NB), Decision Tree (DT), Random Forest (RF), k-Nearest Neighbour (kNN), and Support Vector Machine (SVM). Resulting classifiers were compared by performance and classifier based on Decision Tree algorithm yielded highest accuracy (98.5%) among other tested systems. Obtained results suggest that by introducing ML algorithms in MD management strategies benefit healthcare institution firstly in terms of increase of safety and quality of patient diagnosis and treatments, but also in cost optimization and resource management.

Armstrong, Grayson W., and Alice C. Lorch [42] Ophthalmology as a field is uniquely capable of capitalizing on the benefits of machine learning due to many multimodal imaging studies and clinical metrics available. AI and machine learning have already started to revolutionize computer-assisted diagnosis, screening, and prognostication of both anterior and posterior segment ophthalmic disease, as is exemplified by the first FDA-approved AI algorithm for disease diagnosis being applied to DR screening. Population-based screening programs and telemedicine efforts stand to benefit immensely from these advances, as do clinicians equipped with AI-based decision support tools.

Ahmed, Zeeshan, et al [43] focused on analyzing and discussing various published artificial intelligence and machine learning solutions, approaches and perspectives, aiming to advance academic solutions in paving the way for a new data-centric era of discovery in healthcare.

Castellazzi, Gloria, et al [44] investigated, first, whether different kinds of ML algorithms, combined with advanced MRI features, could be supportive in classifying VD from AD and, second, whether the developed approach might help in predicting the prevalent disease in subjects with an unclear profile of AD or VD. Three ML categories of algorithms were tested: artificial neural network (ANN), support vector machine (SVM), and adaptive neuro-fuzzy inference system (ANFIS).

Aggrawal, Ritu, and Saurabh Pal [45] proposes a sequential feature selection algorithm for detecting death events in heart disease patients during treatment to select the most important features. Several machine learning algorithms (Linear Discriminant Analysis (LDA), Random Forest (RF), Gradient Boosting Classifier (GBC), Decision Tree (DT), Support Vector Machine (SVM), and K-Nearest Neighbor (KNN)) are used.

Verma, Anurag Kumar, Saurabh Pal, and Surjeet Kumar [46] presented a new method, which applies six different data mining classification techniques and then developed an ensemble approach using bagging, AdaBoost, and gradient boosting classifiers techniques to predict the different classes of skin disease. Further, the feature importance method is used to select important 15 features which play a major role in prediction. A subset of the original dataset is obtained after selecting only 15 features to compare the results of used six machine learning techniques and ensemble approach as on the whole dataset. The ensemble method used on skin disease dataset is compared with the new subset of the original dataset obtained from feature selection method.

Battineni, Gopi, et al [47] reviewed applications of machine learning (ML) predictive models in the diagnosis of chronic diseases. Chronic diseases (CDs) are responsible for a major portion of global health costs. Patients who suffer from these diseases need lifelong treatment. Nowadays, predictive models are frequently applied in the diagnosis and forecasting of these diseases. In this study, the authors reviewed the state-of-the-art approaches that encompass ML

models in the primary diagnosis of CD. This analysis covers 453 papers published between 2015 and 2019, and our document search was conducted from PubMed (Medline), and Cumulative Index to Nursing and Allied Health Literature (CINAHL) libraries.

Ström, Peter, et al [48] aimed to develop an artificial intelligence (AI) system with clinically acceptable accuracy for prostate cancer detection, localisation, and Gleason grading. An AI system can be trained to detect and grade cancer in prostate needle biopsy samples at a ranking comparable to that of international experts in prostate pathology. Clinical application could reduce pathology workload by reducing the assessment of benign biopsies and by automating the task of measuring cancer length in positive biopsy cores. An AI system with expert-level grading performance might contribute a second opinion, aid in standardising grading, and provide pathology expertise in parts of the world where it does not exist.

Feeny, Albert K., et al [49] provided the novice reader with literacy of Artificial Intelligence/ Machine Learning (AI/ML) methods and provide a foundation for how one might conduct an ML study. The authors provided a technical overview of some of the most commonly used terms, techniques, and challenges in AI/ML studies, with reference to recent studies in cardiac electrophysiology to illustrate key points. The authors highlighted an important considerations and challenges for appropriate validation, adoption, and deployment of AI technologies into clinical practice.

Hügle, Maria, et al [50] explained the basics of machine learning and its subfields of supervised learning, unsupervised learning, reinforcement learning, and deep learning. The authors provided an overview of current machine learning applications in rheumatology, mainly supervised learning methods for e-diagnosis, disease detection, and medical image analysis.

Thomsen, Kenneth, et al [51] conducted a systematic review of existing literature, identifying the literature through a systematic search of the PubMed database. Two doctors assessed screening and eligibility with respect to pre-determined inclusion and exclusion criteria. The authors presented a complete overview of artificial intelligence implemented in dermatology. Impressive outcomes were reported in all the identified eight categories, but head-to-head comparison proved difficult. The many areas of dermatology where the authors identified machine learning tools indicate the diversity of machine learning.

Mayro, Eileen L., et al [52] Deep learning (DL) is a subset of artificial intelligence (AI), which uses multilayer neural networks modelled after the mammalian visual cortex capable of synthesizing images in ways that will transform the field of glaucoma. Autonomous DL algorithms are capable of maximizing information embedded in digital fundus photographs and ocular coherence tomographs to outperform ophthalmologists in disease detection. Other unsupervised algorithms such as principal component analysis (axis learning) and archetypal analysis (corner learning) facilitate visual field interpretation and show great promise to detect functional glaucoma progression and differentiate it from non-glaucomatous changes when compared with conventional software packages. Forecasting tools such as the Kalman filter may revolutionize glaucoma management by accounting for a host of factors to set target intraocular pressure goals that preserve vision. Activation maps generated from DL algorithms that process glaucoma data have the potential to efficiently direct our attention to critical data elements embedded in high throughput data and enhance our understanding of the glaucomatous process.

Farhadian, Maryam, Parisa Shokouhi, and Parviz Torkzaban [53] aimed to design a support vector machine (SVM) based decision-making support system to diagnosis various periodontal diseases. Data were collected from 300 patients referring to Periodontics department of Hamadan University of Medical Sciences, west of Iran. Among these patients, 160 were Gingivitis, 60 were localized periodontitis and 80 were generalized periodontitis. In the designed classification model, 11 variables such as age, sex, smoking, gingival index, plaque

index and so on used as input and output variable show the individual's status as a periodontal disease. Using different kernel functions in the design of the SVM classification model showed that the radial kernel function with an overall correct classification accuracy of 88.7% and the overall hypervolume under the manifold (HUM) value was to 0.912 has the best performance. The results of the present study show that the designed classification model has an acceptable performance in predicting periodontitis.

Ahn, Joseph C., et al [54] provided a comprehensive overview of hepatology-focused AI research, discussed some of the barriers to clinical implementation and adoption, and suggest future directions for the field.

Ahmed, Hager, et al [55] presented a real-time system for predicting heart disease from medical data streams that describe a patient's current health status. The main goal of the proposed system is to find the optimal machine learning algorithm that achieves high accuracy for heart disease prediction. Two types of features selection algorithms, univariate feature selection and Relief, are used to select important features from the dataset. The authors compared four types of machine learning algorithms: Decision Tree, Support Vector Machine, Random Forest Classifier, and Logistic Regression Classifier with the selected features as well as full features. The authors applied hyperparameter tuning and cross-validation with machine learning to enhance accuracy. One core merit of the proposed system is able to handle Twitter data streams that contain patients' data efficiently.

4. PROBLEM STATEMENT

The accurate prediction of survival rate in patients with diseases remains a challenge due to the increasing complexity of disease, treatment protocols, and various patient population samples. Reliable and well-validated predictions could assist in a better way personalized care and treatment and improve the control over the cancer development. There is a definite increase in the use of classification-based approaches in contemporary medical diagnostics. At first sight, all these classification-based approaches use various and heterogeneous medical data and can inflate the quality of diagnostics. On the contrary, numerous recent developments in computer science, data science, and ML assist in the decrease of errors in overall diagnostics. The use of artificial intelligence techniques for classification in medical studies provides more informative knowledge-based background for prediction and prognosis of disease to be tested more meticulously and rapidly, in a short time.

5. RESEARCH DIRECTION

There is an intensive and rapid development of new knowledge-based diagnostic methods for disease detection with the extended use of tools of bioinformatics, computer science, statistics, and machine learning. Aside from that, many of these methods are difficult for integration and combination in a meaningful workflow. With the advent of a large development and application of machine learning (ML) methods in the medical studies, they have become more accurate and based on the discovery of new enriched knowledge about origin, classification, prognosis, and therapy.

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